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A Fuzzy Neural Network Based Dynamic Data Allocation Model on Heterogeneous Multi-GPUs for Large-scale Computations

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Abstract: The parallel computation capabilities of modern graphics processing units (GPUs) have attracted increasing attention from researchers and engineers who have been conducting high computational throughput studies. However, current single GPU based engineering solutions are often struggling to fulfill their real-time requirements. Thus, the multi-GPU-based approach has become a popular and cost-effective choice for tackling the demands. In those cases, the computational load balancing over multiple GPU "nodes" is often the key and bottleneck that affect the quality and performance of the real-time system. The existing load balancing approaches are mainly based on the assumption that all GPU nodes in the same computer framework are of equal computational performance, which is often not the case due to cluster design and other legacy issues. This paper presents a novel dynamic load balancing (DLB) model for rapid data division and allocation on heterogeneous GPU nodes based on an innovative fuzzy neural network (FNN). In this research, a 5-state parameter feedback mechanism defining the overall cluster and node performance is proposed. The corresponding FNN-based DLB model will be capable of monitoring and predicting individual node performance under different workload scenarios. A real-time adaptive scheduler has been devised to reorganize the data inputs to each node when necessary to maintain their runtime computational performance. The devised model has been implemented on two dimensional (2D) discrete wavelet transform (DWT) applications for evaluation. Experiment results show that this DLB model enables a high computational throughput while ensuring real-time and precision requirements from complex computational tasks.

Keywords: Heterogeneous GPU cluster, dynamic load balancing, fuzzy neural network, adaptive scheduler, discrete wavelet transform.

1 Introduction

In the last decade, the powerful parallel computing capabilities of graphics cards and GPUs, originally driven by the market demands for real-time and high-definition game displays, have been widely accepted by the research communities. Large scale and data intensive computational applications such as areal surface characterization filtration, visual recognition, and natural language processing (NLP), have been benefitted by this newly-found and cost-effective computational powerhouse. It has also attracted increasing attentions from researchers across the globe in devising general hardware-based acceleration models for real world engineering challenges[1−3]. Leading the trend, in 2007, NVIDIA released the Compute Unified Device Architecture (CUDA) – a software framework that aimed at unifying the efforts in harnessing the GPU powers for general-purpose usages and special applications. It has greatly simplified the GPU programming practices as well as embracing the inherent data parallelism from GPU architectures. The toolkit has significantly enhanced the performance of some of the most common data and signal processing functions such as fast fourier transform (FFT), Gaussian filtering, and discrete wavelet transform (DWT) that are widely used in applications such as face detection, DNA sequencing, and more recently, machine learning systems such as convolutional neural networks[4−6].

CUDA provides a scalable and integrated programming model for allocating and organizing processing threads and mapping them onto the computer hardware infrastructure equipped with dynamical adaptation ability for all mainstream GPU architectures[7]. In addition, CUDA has linked and embedded a series of interfaces and APIs to assist direct programming on GPUs instead of relying on various graphics APIs (e.g., OpenGL) like in the so-called "GPGPU" era. CUDA treats GPU as a standalone parallel computational device that can realize data processing algorithms by using

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C/C++-like programming routines and functions that are familiar to mainstream programmers and researchers.

Previous related works on parallelizing processes and data were mainly achieved through using a single GPU that had witnessed a moderate performance gain across the board. However, due to the limitation of data storage format and space (memory), as well as the fixed number of data streams available on a single GPU, previous works are often struggling to fulfill the real-time requirements from many large scale computational applications, this is especially problematic for the latest deep learning applications that often require to process data sets with tens of gigabytes (GB) in size (e.g., ImageNet)[8−10], never mentioned the online areal surface texture measurement tasks for processing surface texture data engaging complex filtration with a large number of numerical tolerance parameters (e.g., processing a data set with multi-level DWT)[11, 12]. Thus, in comparison, multi-GPUs based acceleration solutions can be flexible to achieve higher performance with relatively low hardware costs. Numerous computational-intensive issues that cannot be resolved by using the single GPU model have been making steady progress in the context of multi-GPUs, e.g., multi-GPUs based FFT[13] and Gaussian filtering[14]. In the meantime, several multi-GPUs based programming libraries (e.g., MGPU)[15] and MapReduce libraries (e.g., GPMR and HadoopCL)[16, 17] have been developed by researchers in the field.

It is a challenging task to fully utilize the parallel computational power of multiple and interconnected GPU nodes[18], which is especially true for the heterogeneous multi-GPU systems. Unbalanced load problem may cause low computational performance. To solve this problem, the load balancing models that can intelligently allocate tasks to individual GPU node are becoming the key solutions. Chen et al.[19] proposed a task-based DLB solution for multi-GPU systems that can achieve a near-linear speedup with the increasing number of GPU nodes. Acosta et al.[20] had developed a DLB functional library that aims to balancing the load on each node. However, these pilot studies are based according to the corresponding system runtime performance on the assumption that all GPU nodes equipped in a multi-GPU platform have equal computational capacity. In addition, task-based load balancing schedulers that these approaches have relied upon often fall short to support applications with huge data throughputs but limited processing function(s) – there are very few "tasks" to schedule, e.g., DWT. These applications need more attention in refining the task partition in each computational iteration taking into account of the data locality[18]. In terms of data parallelism based load balancing schedulers, Acosta et al.[21] presented a DLB model that dynamically balances the workload using information established by the first iteration of the computation, which failed to respond to the information changes during the later computational iterations. In contrast, the strategies developed by Boyer et al. and Kaleem et al. collect system information during the system runtime[18, 22, 23], so they can support the dynamic load balancing scheduling demands according to the real-time feedback, which consolidate the foundation for this study.

To optimize the load balancing problem among multi-GPU nodes for large scale applications with highly repetitive computational procedures or iterations, this paper presents a novel DLB model based on fuzzy neural network (FNN) and data set division techniques for heterogeneous multi-GPU systems, and this study is extended from our previous publication[24]. In this study, five real-time state feedback parameters closely relating to the computational performance of every GPU node are defined. They are capable of predicting the relative computational performance of each GPU node during system runtime. Using the constructed FNN and the devised advanced data distribution method, a large data set can be adaptively divided to enhance the overall utilization of all hidden computing powers from a heterogeneous multi-GPU system.

The rest of this paper is organized as follows. Section 2 presents a brief review over the preliminaries and related works in the field. Based on the literatures, the rationales of this research are justified; The proposed FNN DLB model for multi-GPUs is explored and its features are discussed in Section 3. Section 4 constructs a case study that demonstrates how to improve the computational performance of the lifting scheme of DWT by using the devised model. Section 5 provides the test results of the design and evaluations. Finally, Section 6 concludes the research with future works.

2 Related studies

2.1 GPU architectures and process model

Modern GPUs are not only powerful graphics engines, but also highly parallel arithmetic and programmable processors. More significantly, in 2007, NVIDIA introduced the Tesla architecture, which was the first unified graphics and computing architecture. After that, NVIDIA released series of GPU architectures, i.e., Fermi, Kepler, Maxwell, Pascal, and most recently, the Volta architecture. All GPU cards produced by NVIDIA in the last decade are based on these architectures. In the point of view of the hardware architectures, all these models are similar but with incremental improvements on memory sizes and their accessibility, the overall processing powers, and number of streaming multiprocessors (SM) that each contains multiple stream processors (SP, also named CUDA cores) and special-function units (SFU). Modern GPU architectures are based on a scalable processor array formed by SPs that provides a high performance parallel computing platform.

CUDA is a parallel programming framework that was designed especially for general purpose computing, and it greatly simplifies the GPU programming practices. CUDA adopts a SPMD (single program, multiple data) programming model and provides a sophisticated memory hierarchy (i.e., register, local memory, shared memory, global memory, texture memory, constant memory, etc.). Hence, a GPU can achieve high data parallel computation through elaborately designed CUDA codes empowered by the efficient usage of different memories according to the respective data features, including access mode, size and format.

The computational capacity of a single GPU can sometimes satisfy the computational demands of numerous applications, for example in the conventional image filtering and other transformation processes. However, it is still falling short of processing some complex tasks engaging massive data sets, for example in video indexing and visual recognition, due to its limited memory space, instruction length, and execution loops. One perceived solution is to deal with large volume data sets in distributed processing mode on multi-GPUs. At present, there are two representative categories of multi-GPU platforms, the standalone computer type (a single CPU node with multiple GPU processors), and the cluster type (multiple CPU nodes and each accompanied by one or more GPU processors). In general, the cluster computer systems require more complex communication and data transmission due to their commonly adopted peripheral component interconnect express (PCI-E) architecture and network connections. Thus, the standalone computers have been chosen in this research.

2.2 Fuzzy neural network

Artificial neural network (ANN) is a branch of artificial intelligence (AI) that was first inspired by the "understanding" of how human brain works to process data and summarizes patterns. In contrast with traditional methods that have to extract features from input data in a rigid and almost mechanical manner, ANN based models can automatically find features from training data, which are called "learning from data". One of successful applications relating to ANN is deep learning (DL) based on a process model called deep neural network, e.g., Krizhevsky presented the AlexNet to classify images in ILSVRC2012 (the ImageNet Large-scale Visual Recognition Challenge) and achieved the winning performance with the test error rate of 15.3%[8]. AlexNet is considered as the first successful DL model. Later, in 2015, He et al.[25] presented a new DL model, ResNet, that won the ILSVRC 2015 with an incredible error rate of 3.6%.

Generally speaking, traditional fuzzy systems are built on IF-THEN rules (i.e., fuzzy rules) which are acquired from experimental knowledge of domain experts. Fuzzy systems can solve complex decision-making issues when equipped with abundant fuzzy rules[26]. Li et al.[27] designed a fuzzy keyword search engine based on a fuzzy system for searching encrypted data over cloud sources, and it solved the drawback of traditional techniques that struggled to match keywords on cloud. Krinidis et al.[28] had improved the fuzzy C-Means (FCM) algorithm and presented fuzzy local information C-Means (FLICM) algorithm based on fuzzy set theory for image clustering. Compared with FCM, FLICM is more effective and efficient, which provides robustness to noisy images clustering.

Both fuzzy theory and ANN have been widely used in decision-making applications. However, the main problem of traditional fuzzy systems is that it is very difficult to find experts who can extract and summarize knowledge from their experiences, and extracted IF-THEN rules are usually not objective, which means that traditional fuzzy models are lacking of flexibility and robustness. Furthermore, the ANN models are still inadequate in representing the expert experiences. To solve these shortcomings, fuzzy neural network was developed to combine the fuzzy rule based fuzzy systems and ANNs. Thus, ANN models have been merged into fuzzy systems to improve their efficiency and accuracy, such that FNN was envisaged to be a promising model[29]. Kuo et al.[30] proposed a FNN based decision support system of intelligent suppliers which is able to consider both the quantitative and qualitative factors. Chen et al.[31] used FNN to approximate unknown functions in stochastic systems, which not only reduced the online computation load, but also achieved significant performance enhancement for fuzzy control algorithm.

Fuzzy theory and ANN based load balancing approaches have been widely used in traditional multi-CPU systems, i.e., distribution systems, data centers, cloud computing applications, etc. Saffar et al.[32] presented a fuzzy optimal reconfiguration approach that combines fuzzy variables and ant colony search method to balance the workloads on distribution systems. Susila et al.[33] developed a fuzzy based firefly approach for dynamical load balancing purpose in cloud computing systems. Toosi and Buyya[34] proposed a fuzzy logic based DLB model for cost and energy efficient purposes. These prior works have inspired the motivation of adopting FNN for multi-GPU load balancing applications investigated in this study.

In summary, based on the achievements of previous related works, it is anticipated as a feasible way to solve the DLB issue by adopting the FNN model. This study explores and implements a novel data-oriented load balancing model by devising a FNN framework for large data sets with simple iterative tasks on heterogeneous multi-GPU systems.

2.3 Conventional multi-GPU strategies

Fig. 1 demonstrates a traditional load balancing model based on the pure data set division method[2], where: 1) A large raw data set is divided into n small chunks (subsets) (n is equal to the number of GPU nodes in a targeted multi-GPU system), and each data chunk is distributed to a GPU node respectively; 2) Each GPU node processes the corresponding subset; 3) The final results can be generated after merging the outputs of each GPU node. This approach is very simple and useful, however, it is likely to cause unbalanced load problem when the multi-GPU system contains different types of GPU hardware with unequal computational performance, known as heterogeneous multi-GPU platforms. As a result, the overall performance of a multi-GPU platform is restricted to the GPU node that has the lowest computational capability due to delayed merging process.

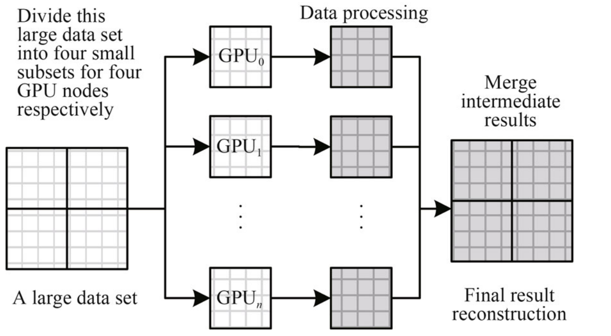
Divide this large data set into four small subsets for four GPU nodes respectively
Data processing
GPU$_0$
GPU$_1$
GPU$_n$
Merge intermediate results
A large data set
Final result reconstruction

Fig. 1 A traditional load balancing model based on the pure data division method

In a heterogeneous multi-GPU system, there are different types of GPUs having unequal computational performance, e.g., the multi-GPU workstation used in this study has two GPU cards – a middle-low-end (NVIDIA GTX 750 Ti) and a high-end GPU (NVIDIA GTX 1080). As the traditional data division method is still struggling to support heterogeneous multi-GPU systems, Acosta et al.[21] developed a DLB library (named ULL_Calibrate_lib) for heterogeneous systems aiming to solve the task allocation problem. ULL_Calibrate_lib can balance tasks dynamically to adapt system conditions during execution. This approach shows sound results for iterative operations, but has low performance when dealing with applications of large data throughputs with limited processing instructions – the too few "tasks" problem for the scheduler. For example, in surface metrology, metrologists often apply DWT functions to extract the surface texture characteristics from large volume of measured data[35]. Thus, in these cases, a data-oriented load balancing model is more suitable than the task-focused ones.

Boyer et al.[18] explored a data-oriented DLB approach that supports GPU programs having a few kernels to process large volume data set iteratively. The main idea of Boyer′s work is to predict the potential computational performance of each GPU node, and then divide the remaining data set according to the execution time of each GPU node for processing its previous assigned data set: 1) The host function sends initial small data chunks respectively for each GPU node and launches the corresponding kernels of each GPU. Assuming there are two GPU nodes in a multi-GPU system, a small data chunk is D, t_i indicates the processing time of the i-th GPU and C_i is the corresponding potential performance of the i-th GPU, then

$$C_i = \frac{D}{t_i}. \tag{1}$$

2) The host function divides the remaining data for each GPU node. Let W be the remaining data set to be scheduled and W_i indicates the data set for i-th GPU, then

$$W=\sum_i W_i. \tag{2}$$

In the balanced situation, all GPU nodes should finish their computations at the same time satisfying the following equation:

$$C_1W_1=C_2W_2. \tag{3}$$

According to (1) and (3), W_i can be given as:

$$W_1=\frac{t_1W_2}{t_2}. \tag{4}$$

One of the drawbacks of this load balancing model is that it is disputable whether the initial execution time can accurately predict the real computational ability of a GPU. More specifically, a modern GPU card can have hundreds or even thousands of CUDA cores, e.g., NVIDIA GTX 750 Ti contains 640 cores, and NVIDIA GTX 1080 has 2560 cores. As a result, a small data set may cause a low GPU utilization rate, which causes the inaccurate performance prediction. For instance, in this study, we tested and evaluated the execution time for processing a small surface measurement data set by using DWT on these two GPUs respectively, experimental result shows that the processing time of these two GPUs are almost the same because both of them cannot fully use their hardware resources as there are not enough data to process. In this case, the data allocated on each GPU node will be of the same size by using (4), which is not different from the pure data set division method (see Fig. 1). In addition, these previous load balancing models failed to respond to the fluctuation of computational performance that is frequently occurred on multi-GPU systems in the real world.

The proposed DLB model in this paper aims at predicting the computational performance according to the real hardware conditions rather than testing the processing time with a small data set, such that it improves the accuracy of performance prediction and supports real-time response to the fluctuation of computational performance.

3 Load balancing on heterogeneous multi-GPU systems

3.1 DLB idealism

To solve the unbalanced load problem and to respond to the fluctuation of computational performance from a heterogeneous multi-GPU system, this paper presents a novel DLB model for optimizing the overall parallel computational performance of large scale data computations on multi-GPU systems while ensuring the good price-performance ratio based on the FNN and dataset division method. In this model, the original data set is divided into several equal-sized data units and these data units are organized into n groups (n is equal to the number of GPU nodes in a specific multi-GPU platform) by using the scheduler, see Fig. 2. The number of data units assigned to each GPU

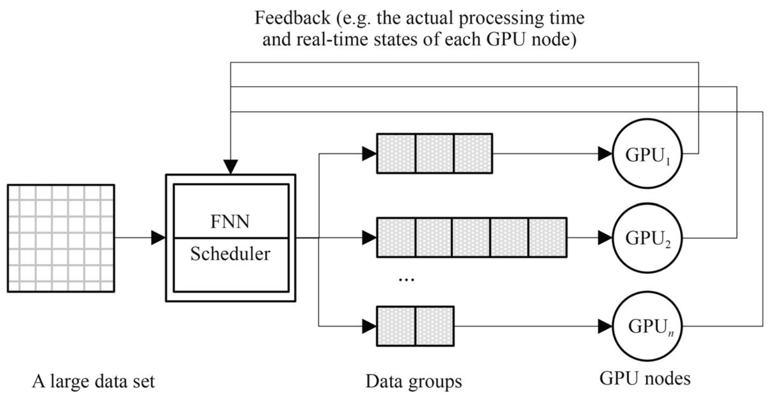
Feedback (e.g. the actual processing time and real-time states of each GPU node)
FNN
Scheduler
GPU1
GPU2
...
GPUn
A large data set
Data groups
GPU nodes

Fig. 2 The overall framework of the proposed data based DLB model

node is different, and it is determined by the real-time feedback (e.g., real-time computational performance and states of each GPU node) of a single GPU node. Thus, the purpose of data-oriented DLB model is to minimize the overall processing time by dynamically adjusting the number of data units in a group for each GPU node at runtime according to real-time state feedback of each GPU node.

3.2 Model and workflow

To describe the relationship between the real-time state feedback parameters and the number of data units assigned in a group to be "pushed" to a node, this model defines the relative computational ability CP_i^n to represent the n-th predication of real-time computational performance of i-th GPU node, and the scheduler and CP_i^n is defined as:

$$CP_i^n = f(\frac{D_{unit}}{T_i^{unit}}), \quad CP_i^n \in [0,1], n = 0,1,2,\cdots \tag{5}$$

where D^{unit} is a data unit, T_i^{unit} is a feedback parameter denoting the actual processing time of D_{unit} by the i-th GPU node, and $f(x)$ is a normalization method.

In the ideal load balancing situation, all GPU nodes in a multi-GPU system would finish their respective work at the same time, this idea is the same as Boyer′s model (see (3)), and it satisfies the following equation:

$$\begin{aligned}&T_1{=}T_2{=}\cdots{=}T_m\\ &\quad\Rightarrow T_1^{unit}\times W_1 = T_2^{unit}\times W_2 = \cdots {=} T_m^{unit}\times W_m\end{aligned} \tag{6}$$

where T_i is the total processing time of i-th GPU node in a parallel computational task and W_i is the count of current workload (i.e., the current number of data units) for i-th GPU node. According to (5) and (6), the number of data units can be calculated. Taking two GPU nodes as an example, $T_1 = T_2$, then:

$$\begin{aligned}&T_1^{unit}\times W_1 = T_2^{unit}\times W_2\\ &\quad\Rightarrow W_1 = \frac{T_2^{unit}\times W_2}{T_1^{unit}} \Rightarrow W_1 = \frac{CP_2{}^n\times W_2}{CP_1{}^n}.\end{aligned} \tag{7}$$

The same calculation method can be extended to multiple GPU nodes by using (7). Based on (5)–(7), the complete procedure for dynamically calculating the number of data units for every GPU node in any multi-GPU platform during runtime can be defined as: 1) This DLB model conducts the initial prediction to get CP_i^0 for every GPU node by using the FNN structure after acquiring the original data set (see Figs. 2 and 3); 2) The scheduler calculates the number of data units for each data group according to CP_i^0 by using (7); 3) The multi-GPU platform begins the target parallel computational task when every GPU node gets the corresponding data group organized by the scheduler, and the FNN collects state feedback dynamically to prepare the next predication under certain state; 4) Once a GPU node has finished its data processing while others have not, the model estimates the remaining time (T_i^r) for each GPU node by using (8):

$$T_i^r = T_i^{unit}\times\left(W_i{-}W_i{}'\right) \tag{8}$$

where W_i' is the finished workload of the i-th GPU node; 5) The data group reorganization is required when remaining time of any GPU node exceeds the threshold preset by this model, such that the next predication is required to get CP_i^1; 6) The scheduler reorganizes the remaining data groups for all GPU nodes respectively according to CP_i^1; 7) The steps 2)–6) maintain a complete iteration that will be repeated until that all GPU nodes finish their workloads at the same time or the remaining time for every GPU is under the threshold (i.e., satisfying (6)).

According to (7), it is convenient to divide data units and organize data groups for each GPU node when CP_i^n or T_i^{unit} are given. Unfortunately, CP_i^n or T_i^{unit} can be given only when the whole data processing task is finished. Therefore, precise prediction of CP_i^n is the key factor of the devised model.

3.3 A FNN-driven mechanism

To predict CP_i^n for each GPU node, this research has explored in depth the fundamentals of fuzzy theory and defined a 5-state feedback (the fuzzy sets) parameters namely: the floating-point operations performance (F), global memory size (M), parallel ability (P), the occupancy rate of computing resources of a GPU (UF) and the occupancy rate of global memory of a GPU (UM). Each fuzzy set defines the "high" and "low" fuzzy subsets. Likewise, the n-th relative computational ability CP_i^n is also fuzzified as "high" and "low". All fuzzy sets and subsets are listed in Table 1.

Table 1 Defined fuzzy sets and subsets

Sets	Descriptions	Fuzzy subsets	Descriptions of fuzzy subsets
F	The floating-point operations	FL	Low
	performance	FH	High
M	Memory size	ML	Low
		MH	High
P	Parallel ability (a positive correlation with the count of processor cores of a	PL	Low
	GPU node)	PH	High
UF	The occupancy rate of computing	UFL	Low
	resources	UFH	High
UM	The occupancy rate	UML	Low
	of global memory	UMH	High
CP	The relative computational	CPL	Low
	ability	CPH	High

After defining the fuzzy subsets, this research has designed a network structure of FNN that combines theories of the fuzzy mathematics and the back propagation mechanism from ANN to predict CP_i^n of each GPU node before activating the scheduler to organize the data groups, see Fig. 3. The first layer of the design is an input layer while the second layer, third layer and fourth layer are considered to be the fuzzy input layer, hidden layer and output layer respectively in the classic structure of back propagation networks. This FNN structure has ten fuzzy truth values as inputs and two fuzzy truth result values as outputs. The final layer (i.e., fifth layer) decodes the fuzzy truth values to the correct value which is the actual CP_i^n of i-th GPU′s and n-th predication. The devised FNN uses I_i^j to denote the input of the i-th artificial neuron in the j-th level layer, O_i^j to denote the output of the i-th artificial neuron in the j-th level layer, w^i to denote weights of connections between the second and third layer, w_i' to denote weights of connections between the third and fourth layers, and w_i'' to denote weights of connections between the fourth and fifth layers (see Fig. 3). The workflows of the corresponding inputs and outputs are illustrated in Fig. 3.

Input layer. The input layer collects real-time states of a GPU node and generates values of the five state feedback parameters (see Table 1) as inputs when a predication of CP_i^n is required. The input layer merely imports real-time state feedback parameters into the FNN, and the input-output formula shows as the following:

$$O_i^1 = I_i^1 = x_i \tag{9}$$

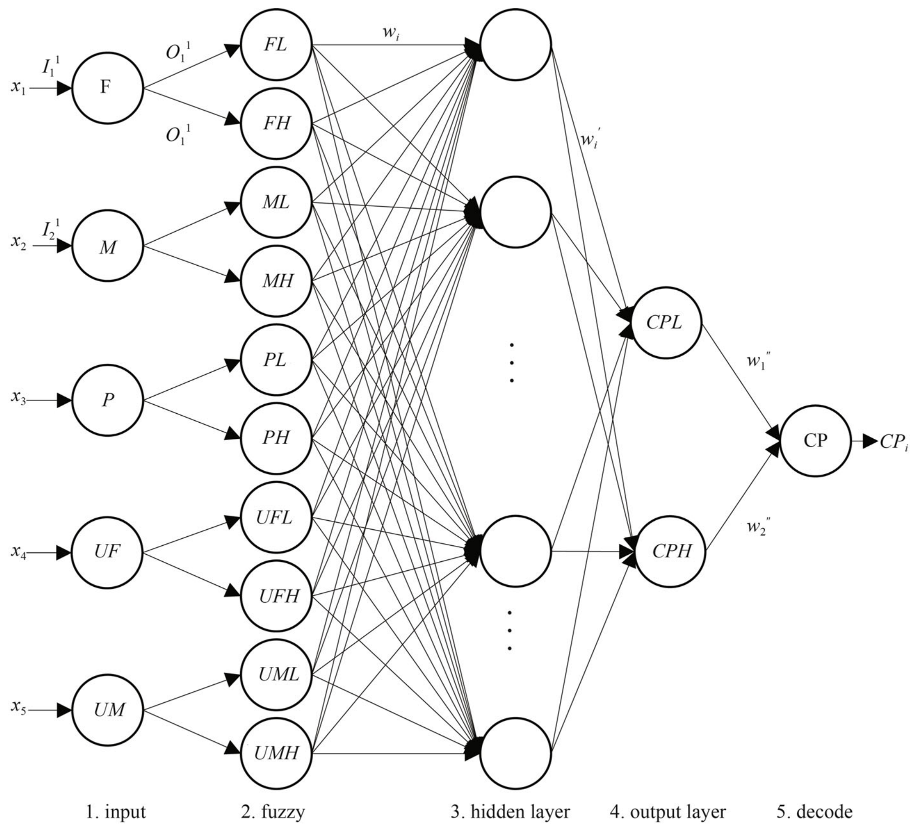

Fig. 3. The structure of FNN in the proposed data-oriented DLB model

where x_i is corresponding to the values of F, M, P, UF and UM in Table 1, respectively.

Fuzzy layer. The fuzzy layer transforms the correct values into fuzzy truth values by using a membership function. The input and output formulas are illustrated as

$$\begin{aligned} I_i^2 &= O_i^1 \\ O_i^2 &= u_A\left(I_i^2\right), O_i^2 \subset [0,1] \end{aligned} \tag{10}$$

where $u_A(x)$ is the membership function[31]. There are a lot of membership functions available, but this research chose the sigmoid function because its "S" shaped curve can gracefully reflect the fluctuations of computational performance of GPU nodes[36]. The equation of sigmoid membership function is defined as

$$f(x) = \frac{1}{1+\mathrm{e}^{-a(x-c)}} \tag{11}$$

where a and c are constants having different values for different fuzzy subsets. Taking the occupancy rate of computing resources of a GPU node (UF, and $UF \in [0,1]$) as an example, this model takes $a = -15$ and $c = 0.5$, and $a = 15$ and $c = 0.5$ to transform a correct value of UF into its fuzzy truth values of UFL and UFH respectively, so the membership functions of UFL and UFH can be defined as

$$\begin{cases} UFL: u_{UFL}\left(UF\right) = \dfrac{1}{1+\mathrm{e}^{15\times(UF-0.5)}} \\ UFH: u_{UFH}(UF) = \dfrac{1}{1+\mathrm{e}^{-15\times(UF-0.5)}}. \end{cases} \tag{12}$$

According to (12), for instance, when a GPU′s $UF = 0.6$, the membership value of UFL is 0.18, and the membership value of UFH is 0.82, see Fig. 4.

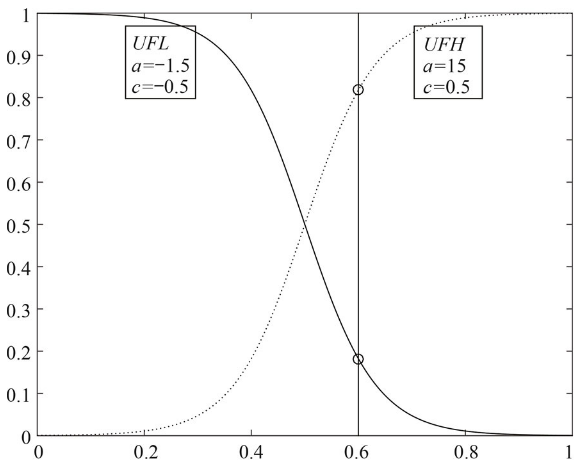

Fig. 4. Membership Functions of UFL and UFH

Hidden layer. In principle, the more the hidden layers, the more complex functions can be fitted. However, it also may cause the disadvantages of a mass of computation and overfitting. Generally speaking, a single hidden layer can meet majority requirements for prediction purposes[36]. Thus, this load balancing model has only one hidden layer. The input and output formulas are defined as

$$\begin{aligned} I_i^3 &= \sum_{j=1}^{n} w_i O_j^2 - \theta_i \\ O_i^3 &= \varphi(I_i^3) \end{aligned} \tag{13}$$

where O_j^2 (n=10) denotes outputs of 10 artificial neurons on the 2nd level layer, and θ_i is a threshold value while $\varphi(x)$ is the activation function used by the artificial neurons. This research has chosen a sigmoid function as the activation function:

$$\varphi(x) = \frac{1}{1+\mathrm{e}^{-ax}}. \tag{14}$$

Output layer. The output layer generates fuzzy truth values of the "high" and "low" fuzzy subsets of CP_i^n. The input and output formulas are defined as

$$\begin{aligned} I_i^4 &= \sum_{j=1}^{m} w_j{}' O_j^3 - \theta_i' \\ O_i^4 &= \varphi\left(I_i^4\right) \end{aligned} \tag{15}$$

where m is the number of artificial neurons on the hidden layer (i.e., the 3rd level layer), θ_i' is a threshold value while the definition of $\varphi(x)$ is the same as (14).

Decode layer. The decode layer is added in this network to transform the fuzzy truth values of the CPL and CPH into the correct value of CP_i^n by using the fuzzy weighted average method. The input and output formulas are defined as

$$\begin{aligned} I^5 &= \sum_{i}^{2} w_i{}'' O_i^4 \\ CP_i = O^5 &= \frac{I^5}{\sum\limits_{i=1}^{2} O_i^4}. \end{aligned} \tag{16}$$

Based on the FNN structure illustrated in Fig. 3, the proposed load balancing model can be learned by training data using the back propagation algorithm that are collected from historical data of real-time state feedback (e.g., data processing time and a GPU states at some point). After the model is trained, it can be used to predict CP_i^n, and then the scheduler can organize the data groups dynamically according to (7).

4 A case study

This data-oriented DLB model supports a wide variety of large scale data computations. This research explores the LWT (lifting wavelet transform) computation for huge metrological data sets of surface textures as a case study to evaluate the validity and efficiency of the proposed model. Rooted in DWT, which is one of the fundamental algorithms for filtration widely used in surface metrology, signal and image processing, biomedicine visualization, and machine vision, LWT aims to improve the computational efficiency through a lifting scheme, also referred as the second generation wavelet[37].

The 1D forward LWT contains four operation steps: split, predict, update and scale[37].

Split. This step splits the original signal into two subsets of coefficients, i.e., *even* and *odd*, and the former one is corresponding to the even index values while the latter is corresponding to the odd index values. The split method is expressed as (17), and it is also called the lazy wavelet transform.

$$\begin{cases} even[i] = X[2i] \\ odd[i] = X[2i{+}1]. \end{cases} \tag{17}$$

Predict. The *odd* coefficients can be predicted from the *even* by using prediction operator P, and then the old *odd* values are replaced by the prediction result as the next new *odd* coefficients recursively. This step can be expressed as (18).

$$odd = odd - P(even). \tag{18}$$

Update. Likewise, *even* coefficients can be updated from the update operator U, and then the old *even* values are replaced by the updated result as the next new *even* coefficients recursively. This step shows as (19).

$$even = even + U(odd). \tag{19}$$

Scale. Normalize *even* and *odd* coefficients with factor K respectively by using (20) to get the results of *evenApp* and *oddDet*, which are the final approximation coefficients and detail coefficients of forward LWT respectively.

$$\begin{cases} evenApp = even \times (1/K) \\ oddDet = odd \times K \end{cases} \tag{20}$$

Table 2 The single-level forward LWT based on CDF 9/7 wavelet

Split	$\begin{cases} even[i] = X[2i] \\ odd[i] = X[2i+1] \end{cases}$
1st predict	$odd[i] - = -\alpha \times (even[i] + even[i+1])$
1st update	$even[i] - = -\beta \times (odd[i] + odd[i-1])$
2nd predict	$odd[i] - = -\gamma \times (even[i] + even[i+1])$
2nd update	$even[i] - = -\delta \times (odd[i] + odd[i-1])$
Scale	$\begin{cases} even = even \times \varepsilon \\ odd = odd \times (1/\varepsilon) \end{cases}$

The inverse LWT with a lifting scheme is achieved by inverting the complete sequence of operation steps of forward LWT and switching the corresponding addition and subtraction operators. With the lifting scheme, the computational results of both forward and inverse LWT for arbitrary wavelet can be obtained through applying several steps of prediction and update operations and the final normalization with factor K, where P_i and U_i represent the i-th prediction and update coefficients respectively (see Fig. 5). For a multi-level DWT, the computational process is repeatedly applied to the approximation coefficients until a desired number of decomposition levels are reached.

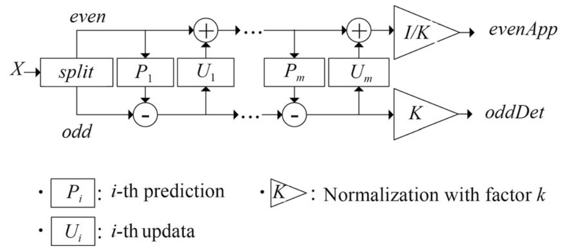

Fig. 5 Main computational procedure of single-level 1D forward LWT

In the case of a 2D DWT, it simply needs to perform the horizontal 1D LWT for each row of a 2D input data set and the vertical 1D LWT for each corresponding column in sequence separately because a 2D LWT can be realized through the 1D wavelet transform along its x-axis and y-axis, such that we can obtain the 2D LWT results: cA, cH, cV and cD; cA is approximation coefficients while cH, cV and cD indicate detail coefficients along horizontal, vertical and diagonal orientations respectively. Fig. 6 illustrates the main computational procedure of a multi-level 2D forward LWT.

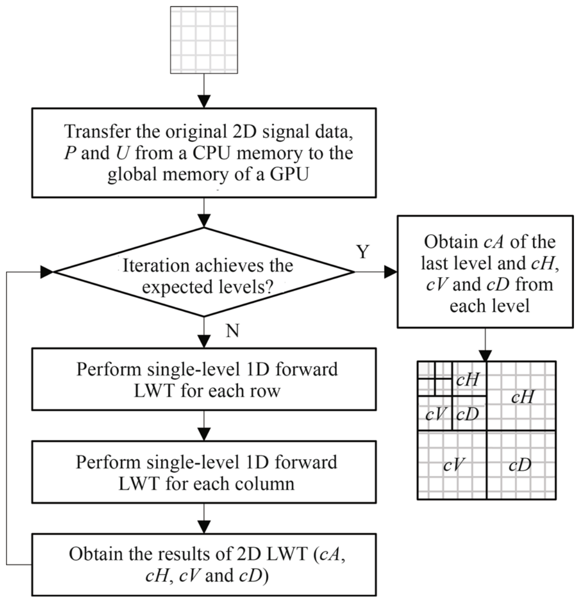
Transfer the original 2D signal data, P and U from a CPU memory to the global memory of a GPU
Iteration achieves the expected levels?
Y
N
Obtain cA of the last level and cH, cV and cD from each level
Perform single-level 1D forward LWT for each row
Perform single-level 1D forward LWT for each column
Obtain the results of 2D LWT (cA, cH, cV and cD)
cH
cV
cD
cH
cV
cD

Fig. 6 Main computational procedure of multi-level 2D forward LWT

Lifting scheme supports variety types of wavelets, and in this case, the research has adopted the CDF 9/7 (Cohen-Daubechies-Feauveau 9/7) wavelet as an example. Table 2 illustrates equations for a single level forward LWT based on the CDF 9/7 wavelet, and its scheduling software routine on a GPU is illustrated in Algorithm 1. The basic idea is that every step of the lifting scheme is performed by different functions, and the CPU program schedules and launches these functions with respect to all data dependencies.

In the context of CUDA and multi-GPU architectures, the overall workflow of LWT computation by using the devised DLB model conforms to Fig. 2, and the scheduler allocates initial data groups of a raw data set to each GPU node, and then GPU nodes process the corresponding data groups with the LWT functions listed in Algorithm 1.

Algorithm 1. The scheduling software routine on a GPU node

```
void $|wt(raw[][])\{$
$//$ Allocating GPU memory
$//$ Transfer data to the global memory of a GPU
$cudaMemcpy(d\_raw,\ raw,\ size,$
    $cudaMemcpyHostToDevice);$
$//$ Split data on GPU
$gpu\_split(d\_even,\ d\_odd,\ d\_raw);$
$gpu\_lwt\_predict(d\_even,\ d\_odd,\ [-alpha,\ -alpha]);$
$//1st$ predict
$gpu\_lwt\_update(d\_even,\ d\_odd,\ [-beta,\ -beta]);$
$//1st$ update
$gpu\_lwt\_predict(d\_even,\ d\_odd,\ [-gamma,\ -gamma]);$
$//2ndpredict$
$gpu\_lwt\_update(d\_even,\ d\_odd,\ [-deta,\ -deta]);$
$//2nd$ update
$gpu\_scale(d\_even,\ d\_odd,\ phi);$
$//Scale$
$//$ Transfer the LWT result from the global memory
    of a GPU
$//$ to CPU memory
$cudaMemcpy(evenApp,\ d_even,\ size,\ deviceToHost);$
$cudaMemcpy(oddDet,\ d_odd,\ size,\ deviceToHost$
    $);$
$\}$
```

5 Test and performance evaluation

5.1 Hardware and test environment

This section analyses the tests and evaluation results of the developed data-oriented DLB model. Table 3 specifies the computer system constructed for the tests which contains two different types of GPU nodes – a middle-low range GPU (NVIDIA GTX 750 Ti) and a high-end GPU (NVIDIA GTX 1080). The proposed model and LWT are realized by using CUDA C/C++ and CUDA Toolkit 8.

Table 3 The specifications of a computer system for the case study

System	Description
CPU	Intel Core i7-4790 3.6GHZ
GPU1	GeForce GTX 750 Ti, 2G
GPU2	GeForce GTX 1080, 8G
OS	Windows 10 64 bit
CUDA	Version 8.0

5.2 FNN training

The FNN can be trained end-to-end by the back propagation and the stochastic gradient descent (SGD) methods. Since there are limited open benchmarks or datasets for multi-GPUs based load balancing models, this study has devised a customizable dataset containing 5-state feedback parameters (see Table 1), the processing data size D and the corresponding actual processing time T. The relative computational ability CP can be given by (21):

$$CP = f(\frac{D}{T}). \tag{21}$$

We randomly initialized the weights for all layers (four layers) from a zero-mean Gaussian distribution algorithm, and trained the FNN in two steps to complete the supervised pre-training and fine-tuning. The first step trained the FNN on 300 data items with the SGD on a learning rate of 0.01. The fine-tuning step then continued the SGD on the learning rate of 0.001 with 200 data items. With this two-step training strategy, the FNN based DLB model has achieved a reliable prediction performance. The comprehensive evaluation of the devised DLB model is further discussed in the following subsections.

5.3 Computation without the DLB model

This section reports test results and evaluates the computational performance of multi-level 2D LWT without applying any DLB models on both single GPU and multi-GPU platforms.

To begin with, this study tested and compared the processing time of a 2D LWT between a single GPU (using either GPU1 or GPU2 respectively) and two GPUs (using both GPU1 and GPU2) environment without employing any DLB models but the traditional division method to divide the data set for each GPU (see Section 2.3). This test performed 4 levels of forward 2D LWT with CDF (9, 7) wavelet on three data sizes $10\,240 \times 10\,240$, $11\,264 \times 11\,264$, to $12\,288 \times 12\,288$. The processing time of each test on three different data sizes had been recorded in Fig. 7. It can be seen from Fig. 7 that the GPU2 setting needs less processing time than the GPU1 setting, and the main reason for this is that the hardware performance of GPU2 is higher than GPU1 – the GPU2 has 2 560 CUDA cores while GPU1 contains only 640 CUDA cores, and the memory storage of GPU2 is also larger than GPU1. According to Fig. 7, the two GPUs (GPU1 & GPU2) setting merely gains limited speedup of about 1.6 times compared with GPU1, and at around 1.3 times compared with GPU2. The detailed processing times for different data sizes by using the two GPUs setting are shown in Table 4 which also indicates the processing time of GPU1 and GPU2 respectively. It can be clearly seen from Table 4 that the overall processing time of the two GPUs setting in the context of the unbalanced load situation is equal to the GPU1-alone situation because the overall computational performance of a multi-GPU platform is ultimately determined by the GPU node with the lowest performance, in this case, the GPU1.

Table 4 The processing times of two GPUs setting with unbalanced implementations (ms)

Data size	GPU1	GPU2	Overall
10 240 × 10 240	2 758	1 500	2 758
11 264 × 11 264	3 876	2 806	3 876
12 288 × 12 288	4 500	3 645	4 500

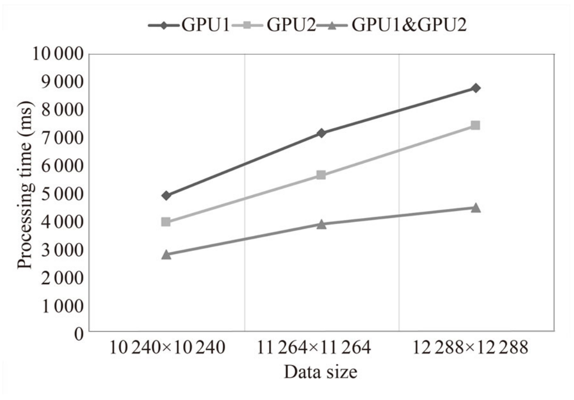

Fig. 7. The computational performance of three test settings

5.4 Computation with the DLB model

Then, this study has tested and compared the computational performance of the 2D LWT operation between the unbalanced implementation (i.e., each GPU node processes one half of a large data set without consideration of its performance variations) and the data-oriented DLB implementation by using the FNN structure in the target multi-GPU system. The processing time of each implementation with different data sizes have been listed in Fig. 8. The processing time of two single GPU settings (i.e., using GPU1 only and GPU2 respectively) where also recorded for comparison. It can be seen from Fig. 8 that the computational performance of the unbalanced implementation has no significant difference comparing with the two single GPU settings. In contrast, the FNN based DLB implementation has gained improvement on computational performances steadily, i.e., it processed a very large data set (e.g., 16 384 × 16 384) in less than one second. Compared with the unbalanced implementation, the peak performance gain (speedup) can reach 12 times which is truly significant. The experimental results show that the proposed data-oriented DLB model can satisfy performance requirements for real-time and large-scale data intensive applications.

5.5 Benchmarking

Lastly, this study carried out a benchmarking test. There are several data oriented DLB models on multi-GPUs, and the Boyer′s model mentioned in Section 2.3 is still considered as the most significant and mainstream strategy for data based DLB according to the latest review papers[22, 38], so the computational performance of the FNN based data-oriented DLB model has been compared with the representative DLB model by Boyer et al.[18] In order to simulate the node performance fluctuations, tasks were assigned to the GPU nodes randomly. The experiment results are shown in Fig. 9 where "stabilization" indicates the steady conditions and "fluctuation" represents the fluctuating conditions. It can be seen from Fig. 9 that both the devised model and Boyer′s model can keep the load (i.e., data allocations) in the balanced situations, and have consistent computational performance when the hardware performance of a multi-GPU platform can keep stable. However, once the hardware performance is perturbed, Boyer′s model struggles to keep up the performance and the processing time increases dramatically (e.g., 12 288 × 12 288 in Fig. 9). In contrast, the FNN based DLB model can resolve the fluctuation problem readily and steadily due to its key feature of predicting and adjusting the current computational performance (CP_i^n) dynamically according to the real hardware condition and feedback.

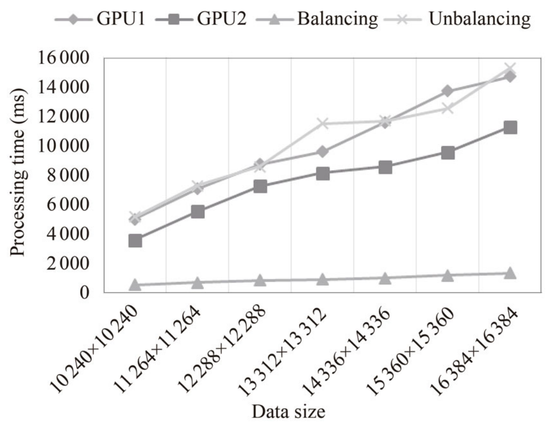

Fig. 8 Comparison of processing times between unbalanced and balancing implementations

6 Conclusions and future work

To fully utilize the parallel computational power of modern GPUs, this paper presents a novel data-oriented DLB model for multi-GPU systems based on an innovative FNN structure and the corresponding dataset division methods. The research started with a comprehensive investigation and analysis of the traditional load balancing models, and concluded with the main drawbacks of them, e.g., the rigidity when dealing with heterogeneous node specifications and configurations. To alleviate the load balancing issues and to effectively respond to the runtime fluctuation of cluster performance, this research has proposed a novel data-oriented DLB model for balancing and optimizing the overall parallel computational performance across multi-GPU nodes. In this model, five state feedback parameters have been identified, and the FNN structure has been implemented to predict the relative computational performance in an adaptive manner. An improved scheduler can then be activated to automate the data allocation tasks according to the relative computational performance across all nodes in a cluster. Experiment results show that the proposed model can achieve substantial computational performance gain when compared with conventional techniques, and the FNN based dynamic model can address the runtime fluctuation issues effectively. The innovative model and its corresponding techniques have addressed the key challenges from large scale computational applications that are often featured by extremely large input volume and highly repetitive operational procedures. Further work will be focused on bridging the flexible FNN idealism across the GPU and CPU boundary, especially when facing the new computing device paradigm of cell CPUs, so as to progressing towards a truly hybrid and efficient task-data distribution scheme for engineering applications.

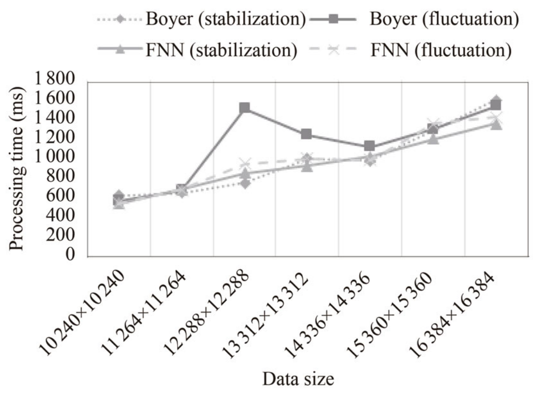

Fig. 9 Comparison of processing time between FNN based DLB model and the Boyer′s model

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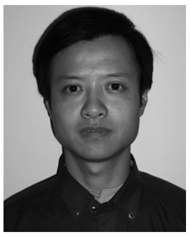

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